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Performance measurement of thermoelectric generating plants with undesirable outputs and random parameters

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ABSTRACT

Conventional paradigms measuring energy efficiency without considering pollution would be biased, as the plants can lose their productive efficiency from the negative output. To rectify this problem, this paper attempts to incorporate both desirable and undesirable outputs in the same model to assess the net efficiency. A distance frontier model is adopted to rank the plants according to their total productivity for the period 1995–2010. Moreover, a random frontier model is adopted to distinguish between homogenous and heterogeneous variables. The results display strong evidence that the rankings of technical efficiency with adjustments for pollution differs significantly from the rankings that do not take pollution into account. Policy implications are derived.

1. Introduction

This paper analyses the technical efficiency of a sample of Portuguese thermoelectric generating plants from 1995 to 2010, with a distance frontier model. The paper allows for negative outputs in the production function adopted and uses the innovative random frontier model [21]. The intention of this study is to obtain reliable and up-to-date measures of thermoelectric generating plants and avoid unrealistic assumptions on the cost-minimising behaviour of the plants, while at the same time accounting for the multi-output nature and heterogeneity of the parameters estimated.

There is a long tradition of analysing electricity plant efficiency. The literature extends from Pollitt [36] data envelopment analysis (DEA) model to recent studies using innovative frontier models [29,13]. Other focus on efficiency includes [11,39,1].

The first of several motivations for the present research is to investigate whether negative outputs change the technical efficiency of thermoelectric generating plants, which generate pollution while generating energy. Pittman [35] was perhaps the first pioneer who treated desirable outputs and undesirable environment pollution in measuring the efficiency of the paper industry with a multilateral index method. Färe et al. [14] conducted a non-parametric efficiency analysis using Pittman's data. Later, Färe et al. [15] applied the homogenous distance frontier model to analyse the negative outputs of the paper and pulp mills. Reinhard et al. [38] treated undesirable outputs in the dairy sector with a stochastic frontier model. Fernandez et al. [17] proposed a stochastic frontier model for technologies exhibiting desirable and undesirable outputs. The next motivation is to generalise the use of undesirable outputs to electricity efficiency, following Yang and Pollitt [44], who analyse Chinese coal-fired power plants' efficiency, allowing for undesirable outputs and using a non-parametric model. Thirdly, a distance stochastic frontier is adopted to handle the multiple outputs and multiple inputs of the technological process [15], but adopting the mixed frontier specification. Frontier models usually aggregate the multiple outputs into a single output, for example, revenue or a multi-lateral superlative index such as the Tornqvist or Fisher indexes [7], or adopt the dual cost function. This second approach is the most common in contemporary frontier research. The distance frontier model overcomes the traditional aggregation problem, which introduces restrictive hypotheses into the analysis. Finally, the mixed frontier model is adopted to distinguish between homogenous and heterogeneous parameters in the estimation of the frontier models [20,21].

The remainder of the paper is organised as follows: Section 2 describes the contextual setting of the analysis. Section 3 presents the literature review. Section 4 explains the theoretical framework, followed by the methodology in Section 5. Section 6 presents the data and results of the study. Section 7 discusses the results and the concluding remarks are made in Section 8.

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2. Contextual setting

The thermoelectric energy plants analysed in the paper belong to the enterprise EDP – Energy of Portugal [5]. EDP presently operates 25 hydroelectric plants and 7 thermoelectric plants dispersed throughout the country. Table 1 displays some characteristics of the plants analysed.

EDP is the major Portuguese electricity production and distribution company. EDP faces competition from the Spanish companies Endesa and Iberdrola, which are the largest electricity producers in the Iberian Peninsula. This competition motivated EDP to buy the fourth-largest Spanish company, Hidroelectrica del Cantabrico, while Iberdrola acquired a stake in EDP in 2004, allowing it to have a non-executive director on the board. EDP's Spanish acquisition needs to be supported by efficiency at company production units, since Hidroelectrica del Cantabrico is a small company in the Spanish market and growth can only be achieved through mergers and acquisitions or productivity improvements that result in larger market share. The new regulation started in 1999 with the establishment of the agency Entidade Reguladora dos Serviços Energéticos (ERSE). With a data span from 1994 to 2004, it was possible to identify the competition and regulatory effects. In 2007, EDP launched a new company, EDP Renewables, devoted solely to producing energy from renewable sources. It currently operates 35 wind farms in Portugal and is the world's third-largest renewable energy producer. In the most recent development, the Portuguese government's 21% stake in EDP was bought by the Chinese Three Gorges company in December 2011 for 2.7 billion euros.

3. Literature review

Efficiency analysis in relation to electricity is concentrated on distribution networks [25,13,12,26]. Papers analysing the efficiency of electricity generating plants include Kleit and Terrell [29], Raczka [37], Hiebert [23], Arocena and Waddams Price [2], Knittel [30]. Jamasb and Pollitt [27] review the frequency with which different input and output variables are used to model electricity distribution. The most frequently used outputs are units of energy delivered, number of customers and size of the service area. The most widely used inputs are number of employees, transformer capacity and network length. The most recent and comprehensive survey of research in energy efficiency can be found in Jamasb et al. [24].

Restricting the literature to papers that analyse undesirable outputs, it is verified that Yaisawarng and Klein [43] apply a DEA model to analyse the effects of SO_2 control on the efficiency change of US coal-fired power plants. Färe et al. [16] analyse the US fossil fuel-fired utilities decomposing the overall productivity in an environmental index and a productive efficiency index. Korhonen and Luptacik [28] analyse 24 coal-fired power plants in Europe, with DEA models allowing for undesirable outputs. Finally, Yang and Pollitt [44] analyse Chinese coal-fired power plants with a DEA multi-stage model.

It is recognised in the literature that both frontier models (DEA and stochastic frontier) give similar rankings. However, previous research has shown that although the DEA scores are inferior in value to econometric scores, the ranking is preserved [6].

Regarding the inputs and outputs, the literature review does not reveal a universally agreed set of input and output variables for the modelling of electricity units [25].

In relation to the efficiency and productivity of EDP, Barros and Peypoch [5] analyse the regulation of EDP hydric with a stochastic frontier model, Barros [3] analyse the EDP hydric with a Malmquist [34] index and Barros and Peypoch [4] analyse the efficiency of EDP thermics with a DEA model.

Recent research on energy performance includes [40,19,42,41,18,33].

Table 1
Characteristics of EDP thermoelectric power plants in 2010. *Source*: EDP accounts.

	Plants	Production (MW h)	Potential value (MW)	Personnel
1	Tapada do Outeiro	613	47	4
2	Carregado	327	710	57
3	Barreiro	200	56	8
4	Setúbal	1688	946	151
5	Sines	9530	1192	333
6	A. Mira	688	132	6
7	Tunes	13498	197	7

4. The theoretical framework

Two competing models of industry efficiency exist in the literature. Firstly, the strategic-group theory justifies differences in efficiency scores as being due to differences in the structural characteristics of units within an industry, which in turn lead to differences in performance. In the case of energy plants, units with similar asset configurations pursue similar strategies, with similar results in terms of performance. While there are different strategic options to be found among the different sectors of an industry, because of mobility impediments, not all options are available to each electricity plant, causing a spread in the efficiency scores of the industry. Secondly, the efficient-structure hypothesis posits that more efficient units charge lower prices than competitors enabling them to capture a larger profit share and economic rents. This hypothesis is a development from the classical structure-conduct-performance hypothesis of Weiss (1974), who suggested a positive relationship between performance and concentration.

Therefore, if the strategic industry theory describes the situation adequately, it should be observed that some plants are more efficient than others, leading to a dispersion of efficiency scores across the units analysed. If the efficient-structure hypothesis holds, it should be observed that market concentration contributes to the efficiency.

5. Methodology

Let the production technology be represented by the production possibility set containing all feasible input and output vectors: $T = \{(x,y)\ x \text{ can produce } y\}$. That is, the output set $P(x)$ can be defined as $P(x) = \{y\colon (x,y) \in T\}$, or inversely, the input set $L(y)$ defined as $L(y) = \{x\colon (x,y) \in T\}$, where $x = (x_1, x_2, \ldots, x_m) \in R_+^m$, and $y = (y_1, y_2, \ldots, y_k) \in R_+^k$.

Assume that both $P(x)$ and $L(y)$ are convex, closed and bounded, and satisfy strong disposability of outputs and inputs. Once the output set (or input set) has been defined, the efficiency can be measured by the distance from observed data point to the best practice (frontier), which can be solved by using either a programming technique or an econometric method.

There are several forms of frontier models [8]. The distance frontier model is based on Shepard (1970). Let the output distance function be defined by the output set $P(x)$ as $D_0(x,y) = \min\{\theta\colon (y/\theta) \in P(x)\}$. In other words, the output distance function $D_0(x,y)$ seeks the maximal ratio that all output quantities could be expanded, given input quantities, while still remaining within the feasible production technology (production possibility set).

Following, we assume that the output distance function $D_0(x,y)$ satisfies the following conditions:

$D_0(x,y)$ is non-decreasing in y and non-decreasing in x.
$D_0(x,y)$ is linearly homogenous and convex in y.
$D_0(x,y) \leqslant 1$, if $y \in P(x) = \{y: y \in P(x)\}$.
$D_0(x,y) = 1$, if $y \in Isoq\ P(x)$.

The distance function $D_0(x,y)$, will take a value which is less than, or equal to, one if the output vector, y, is an element of the feasible production set, $P(x)$. That is, $D_0(x,y) \leqslant 1$ if $y \in P(x)$. Furthermore, the distance function will take a value of unity if y is located on the outer boundary of the production possibility set. That is, $D_0(x,y) = 1$ if $y \in Isoq\ P(x) = \{y: y \in P(x), \omega y \notin P(x), \omega > 1\}$, using the notation that was used by Lovell et al. (1994).

The distance function may be specified with either an input orientation or an output orientation. In this paper, an output orientation is adopted. A Translog function form is specified for the distance frontier, alongside other distance frontier models [22,10,9,32].

The Translog distance function for the case of M outputs and K inputs is specified as:

$$\ln D_{0i} = \alpha_0 + \sum_{m=1}^{M}\alpha_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y_{mi}\ln y_{ni} + \sum_{k=1}^{K}\beta_{kl} \times \ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M}\delta_{km}\ln x_{ki} \times \ln y_{mi} \quad (1)$$

where i denotes the ith plant in the sample and $i = 1,2,\ldots,N$. To obtain the frontier surface D_{0i} is set equal to one, which implies that the left-hand side of Eq. (1) is equal to zero.

The restriction required for homogeneity of degree +1 in outputs is established following Lovell et al. (1994), implying that $D_0(x,\omega y) = \omega\ D_0(x,y)$ for any $\omega > 0$ and one ouput is arbitrarily chosen, such as the Mth output, and set $\omega = 1/y_M$ and Eq. (1) becomes:

$$\ln D_{0i}/y_{Mi} = \alpha_0 + \sum_{m=1}^{M}\alpha_m \ln y^*_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y^*_{mi}\ln y^*_{ni} + \sum_{k=1}^{K}\beta_{kl}\ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M}\delta_{km} \times \ln x_{ki}\ln y^*_{mi} \quad (2)$$

where $y^*_{mi} = y_{mi/y_{Mi}}$.

To facilitate the econometric estimation, Eq. (2) is rewritten as:

$$\ln(D_{0i}/y_{Mi}) = \alpha_0 + \sum_{m=1}^{M}\alpha_m \ln y^*_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y^*_{mi}\ln y^*_{ni} + \sum_{k=1}^{K}\beta_{kl}\ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M}\delta_{km}\ln x_{ki}\ln y^*_{mi} \quad (3)$$

or

$$\ln(D_{0i}) - \ln(y_{Mi}) = \alpha_0 + \sum_{m=1}^{M}\alpha_m \ln y^*_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y^*_{mi}\ln y^*_{ni} + \sum_{k=1}^{K}\beta_{kl}\ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M}\delta_{km}\ln x_{ki}\ln y^*_{mi} + v_i \quad (4)$$

and hence:

$$-\ln(y_{Mi}) = \alpha_0 + \sum_{m=1}^{M}\alpha_m \ln y^*_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y^*_{mi}\ln y^*_{ni} + \sum_{k=1}^{K}\beta_{kl}\ln x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{ki}\ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M}\delta_{km} \times \ln x_{ki}\ln y^*_{mi} + v_i - \ln(D_{0i}) \quad (5)$$

By setting $\ln(D_{0i}) = \mu$ Eq. (5) is exactly identical to the stochastic production function frontier model proposed.

The model is estimated with the maximum likelihood (ML) method [31,8], imposing a half-normal distribution, which signifies that $v_i \sim i.i.d.\ N(0,\ \sigma^2_v)$, e.g. the v_i are independently and identically distributed normal random variables with zero mean and constant variance, and $\mu_i \sim i.i.d.\ N(0,\ \sigma^2_\mu)$, e.g. u_i are independently and identically distributed half-normal random variables, which are truncated at zero and with constant variance. Because v_i are independent of u_i, one can estimate the parameters and inefficiency terms of Eq. (5) by ML.

Young's theorem requires the symmetry restrictions, which correspond to: $\pi_{kr} = \pi_{rk}$ for all k and r, and $\delta_{js} = \delta_{sj}$ for all j and s.

These restrictions reduce the number of parameters to be estimated.

Moreover, the cost function must be non-increasing and convex with regard to the level of fixed input and non-decreasing and concave with regard to prices of the variable inputs. These conditions were not imposed, but may be inspected to determine whether the cost function is well-behaved at each point within a given data set.

To allow direct interpretation of the first-order Translog parameters as elasticities evaluated at the sample mean, every series was divided by its average.

6. Data and results

To estimate the cost frontier, a balanced panel data on EDP thermoelectric production plants for the years 1995–2010 (7 plants × 16 years = 112 observations) was used.

Frontier models require the identification of outputs (transformation of resources) and inputs (resources). Several criteria can be used. One empirical criterion is availability of data. Literature surveys ensure the validity of the research and are therefore another criterion to take into account. Finally, the opinions of professionals working in the sector are of value in the identification of inputs and outputs. In this paper, all three of these criteria were obeyed.

Thermoelectric plants produce energy based on the oil retained, which generates pollution when it burns. Therefore, the outputs are "energy produced in KWh", and plant capacity in MW. These outputs are intensively used in energy research [27].

The inputs were labour, book value of premises, investment and operational costs. These inputs are intensively used in energy efficiency [27,4]. Negative outputs were the emission of air pollution in tons and the emission of water pollution in tons. Pollution emissions are compulsory monitored by the energy plant. Two kinds of pollutions are emitted by thermic plants, the air pollution that generates heated water and turns it into steam and spins a steam turbine which drives an electrical generator. After it passes through the turbine, the steam is condensed in a condenser and recycled to where it was heated; this is known as a Rankine cycle and the smoke stack from an electric power plant containing sulphur dioxide, nitrogen and oxides. A large part of human CO_2 emissions comes from fossil fuelled thermal power plants. Restriction on emissions limits encourages more efficient generation technology and operations by making efficiency count towards meeting emission limits. More efficient technology contributes to pollution

prevention and, hence, lowers emissions of all pollutants. The air pollution is measured as tons of steam not discriminating among the types of emissions. Water emissions aim to cool the system.

Water used for this purpose does cool the equipment, but at some time, the hot equipment heats up the cooling water, which cannot released for the environment while it is hot. The pollution is derived from the hot and some oil that sometimes incidentally contaminates the water and higher water temperature increases plant growth rates. These negative inputs were used by Barros and Peypoch [4] with a DEA model.

Based on the data span available, a stochastic generalised Translog production function was estimated. The variables were transformed according to the description column in Table 2. We adopted the traditional logarithm specification to allow for the possible non-linearity of the frontier.

6.1. Results

In this paper, the Translog production frontier was used, including a deterministic time trend (T) in the estimation of a cost frontier function. The trend may be linear or non-linear and the specification can allow for interactions between time and other explanatory variables, output (y) and inputs (x). The coefficients of the time trend are interpreted as measures of technical change. Table 3 displays the results from the model.

It is verified that the Translog production function specified above fits the data well, as the R-squared from the initial ordinary least-squares estimation that was used to obtain the starting values for the maximum-likelihood estimation is in excess of 92% and the overall F-statistic is 325.12. It is also verified that the variables have the expected signs, with the operational cost increasing with the price of labour and price of capital and water used. Moreover, the total production increases with undesirable outputs and inputs. Furthermore, the cross-variables explain the total cost. Finally, the frontier parameters are all statistically significant and the inefficient error term (λ) being 25% of the total variance.

6.2. Efficiency rankings

Table 4 below presents the results of the time-invariant efficiency scores computed from the residuals. Technical efficiency is achieved, in a broad economic sense, by the unit which allocates resources without waste and thus, the concept refers to a situation on the frontier. Units with a score equal to one are on the cost frontier of best practices, while those with a score lower than one are above the frontier. The value for the unit in the frontier results from a traditional normalisation of the efficiency scores between zero and one adopted in econometric frontiers [31]. The value of waste is measured by the difference between one and the score.

It is verified that the mean score is 97.5% for the efficiency scores without pollution. With pollution, the mean technical efficiency score drops to 0.845. This score suggests that technical efficiency of the thermoelectric generating plants depends on pollution outputs. Therefore, the control of pollutants will permit

Table 3
Stochastic Translog panel production frontier (dependent variable Ln of production).

Homogenous variables	Model without pollution Coefficients (t-ratio)	Model with pollution Coefficients (t-ratio)
Constant	−3.205 (−3.128)*	−2.125 (−2.931)
Trend	0.125 (3.512)*	0.021 (3.782)
Ln AirPollution	–	–
Ln WaterPollution	–	–
Ln Personnel	0.167 (4.178)	0.120 (3.219)
Ln Capital	0.218 (3,192)	0.183 (3.176)
1/2Trend^2	−0.128 (−3.162)*	−0.089 (−3.932)
1/2Ln AirPollution^2	–	0.129 (4.129)*
1/2Ln WaterPollution^2	–	0.271 (4.219)*
1/2Ln Personnel^2	−0.571 (−1.712)**	−0127 (3.218)
1/2Ln Capital^2	−0.251 (−4.128)*	−0.217 (−3.183)
Ln Trend * Ln AirPollution	–	0.018 (1.218)
Ln Trend * Ln WaterPollution	–	0.0218 (0.321)
Ln Trend * Ln Personnel	0.579 (2.626)*	0.319 (4.129)
Ln Trend * Ln Capital	1.076 (2.229)*	1.212 (3.219)
Ln AirPollution * Ln WaterPollution	–	0.021 (0.126)
Ln AirPollution * Ln Personnel	–	−0.257 (−2.783)*
Ln AirPollution * Ln Capital	–	0.217 (3.129)*
Ln WaterPollution * Ln Personnel	–	0.068 (3.821)*
Ln WaterPollution * Ln Capital	–	0.783 (3.215)*
Ln Personnel * Ln Capital	1.321 (4.219)	1.010 (3.674)
Mean for random parameters		
Ln AirPollution	–	−0.216 (−3.124)*
Ln WaterPollution	–	0.231 (3.018)
Scale parameters for distribution of random parameters		
Ln AirPollution	–	−0.143 (4.536)
Ln WaterPollution	–	−0.672 (5.218)
Statistics of the model		
$\sigma = [\sigma_V^2 + \sigma_U^2]^{1/2}$	0.382 (3.315)*	0.215 (4.219)
$\lambda = \sigma_U/\sigma_V$	0.253 (4.521)*	0.312 (3.528)
Log likelihood	124.523	153.218
Chi Square	144.218	218.321
Degrees of freedom	3	3
Probability	0.0002	0.0001
Observations	112	112

t Statistics in parentheses are below the parameters, those followed by * are significant at the 1% level.

Table 4
Efficiency scores.

Thermoelectric plants	Efficiency scores without pollution	Efficient scores with pollution
Tapada do Outeiro	0.998	0.852
Carregado	0.995	0.812
Barreiro	0.990	0.832
Setúbal	0.999	0.852
Sines	1.000	0.932
A. Mira	0.990	1.000
Tunes	0.853	0.832
Mean	0.975	0.845
Median	0.995	0.832
Std. dev	0.054	0.080

Table 2
Descriptive statistics of the data.

Variable	Description	Minimum	Maximum	Mean	Standard deviation
Ln production	Natural logarithm of production in MW h	0.690	6.979	6.200	6.470
Ln capacity	Natural logarithm of capacity in MW	1.671	3.076	2.670	2.645
Ln AirPollution	Natural logarithm of CO_2 produced by each plant in tons	0.01	0.82	0.63	0.19
Ln waterpollution	Natural logarithm of water expelled by the plant in litres	0.01	0.15	0.05	0.04
Ln personnel	Natural logarithm of personnel	0.610	2.623	1.966	2.125
Ln capital	Natural logarithm of the book value of premises at constant price, 2000 = 100	7.579	9.115	8.640	8.621
Trend	Trend variable that varies along the period	1	11	6	3.316

the plants to decrease their output cost by 0.975 − 0.845 = 0.130, without decreasing their input, which, in this case, is labour and capital. The maximum thermoelectric plant score was naturally 1, which was achieved by Sines without taking pollution into account and Alto do Mira when pollutants are taken into account.

7. Discussion

This paper has proposed a simple framework for the evaluation of EDP thermoelectric generating plants and the rationalisation of their management activities, taking into account the traditional output and input descriptors of energy activity. The analysis is based on a distance stochastic production frontier model, allowing for the incorporation of undesirable outputs. Since the paper uses a balanced data set, it presents the efficiency scores for each plant.

How can these results be interpreted? First, it can be concluded that the frontier models with pollutants describe adequately the thermoelectric plants, identifying heterogeneous variables (air pollution and water pollution). The other variables are homogenous. Second, the efficiency rankings displayed by the thermoelectric plants change when pollutants are included in the analysis. This is the main finding of the present paper.

The implication of this result is that a common government policy for thermoelectric plants, in particular policies designed to curb pollution, is unable to reach all units similarly, since heterogeneity exists in relation to the air and water pollutants. Therefore, any economic policy targeting any of these heterogeneous variables has to be tailored by clusters. This is an intuitive result, since thermoelectric plants are not homogenous. They vary in dimension, from small to large, as well as in age, with some plants that are newer and therefore more modern than the old plants. These visible characteristics translate into different performances obtained in the market, resulting in different clusters within the market. These clusters are distinguished from each other by the pollutants produced. These findings also signify that EDP thermoelectric plants are relatively homogenous in terms of labour and capital. With regard to labour and capital, this means that competition over resources drives the market and translates into homogenous dynamics in the labour and capital markets. Additionally, in the case of capital, it signifies that a certain level of investment in capital is a pre-requisite in this market, which translates into homogenous behaviour. Third, the trend square is negative, which signifies that cost increases over time at a decreasing rate. This is an expected result for this industry. Thermoelectric plants are driven by technology improvements based on intense competition observed in the energy market. Thus, a negative sign is expected for the square trend in the production frontier. Fourth, the lambda inefficient parameter signifies that on average, 25% of the production losses are imputable to inefficiency according to the frontier. Moreover the sigma has a value of 38%, signifying a small heterogeneity in this data set. Fifth, the present result clarifies the existence of heterogeneity, the separation between heterogeneity and efficiency [20,21], the cause of different efficiency scores and the role played by undesirable outputs in the efficient frontier.

Finally, in this context, unique assets are seen as exhibiting inherently differentiated levels of efficiency; sustainable production is ultimately a return on the unique assets owned and controlled by the thermoelectric plants. In addition, the strategic-groups theory, which justifies different efficiency scores on the grounds of differences in the structural characteristics of units within an industry, explains part of the efficiency differences observed in the thermoelectric plants.

What should the managers of the thermoelectric plants do to improve efficiency? Firstly, they should adopt a benchmark management procedure in order to evaluate their relative position and to adopt managerial procedures for catching up with the frontier of "best practices". As the frontier is shifting over time, an effort is needed to catch up with it. Secondly, they should curb pollutants not only on ecological, but also economic grounds, since these undesirable outputs contribute to the technical inefficiency. Thirdly, they should adopt a resource-based view of management in order to develop critical resources in strategic issues. However, the adoption of these managerial implications has to take into account the heterogeneity identified in the units analysed.

How does this paper compare with similar research undertaken in other fields? The paper reaches similar conclusions on the role played by undesirable outputs in the frontier [35,14]. Moreover, since it adopts the mixed frontier model, it is comparable with [20,21], but in the present paper, a single frontier model was adopted and homogenous and heterogeneous variables were more clearly separated. Compared with Barros and Peypoch [4] this paper adopts an econometric model and an updated data set, but it validates previous research on energy air and water emissions previous obtained by these authors.

The application of the random frontier model to the thermoelectric power industry can be used as a tool for policy-makers. A regression model that explains factors affecting efficiency scores of the thermoelectric plants was presented, taking into account the heterogeneity in the data set. Finally, an internal benchmark analysis was presented, focusing on Portuguese thermoelectric plants. The stochastic cost frontier model presented lends support to similar works by Kleit and Terrell [29], Knittel [30], Hiebert [23] and Farsi and Filippini [13], although the focus here is on a specific energy asset, i.e., thermoelectric plants.

This paper has one limitation related to the data set. As far as the data set is concerned, the use of a data sample from a single energy company is questionable. Moreover, the data set is short, so that the conclusions are limited. In order for the latter to be more generalised, a larger panel data set would be needed.

A variety of extensions can be made to this paper. Firstly, in view of the heterogeneity identified, a latent production frontier can be adopted in order to identify endogenous segments present in this data. Secondly, a cost frontier model could be applied in order to estimate production efficiency. Finally, an investigation of economies of scale and economies of scope could be conducted.

8. Conclusion

This paper analyses the technical efficiency change of a representative sample of Portuguese thermoelectric plants between 1995 and 2010, a period of intense volatility in the sector. The analysis is based on a random frontier model that allows for the incorporation of undesirable outputs in determining relative efficiencies, together with the separation of homogenous and heterogeneous variables in the cost function. Benchmarks are provided for improving the operations of poorly performing thermoelectric plants.

It was concluded that undesirable outputs are heterogeneous among thermoelectric plants. Energy policy designed to increase the efficiency of these units must take into account this heterogeneity and the role played by undesirable outputs in the frontier of technical efficiency.

The present paper has limitations, which should be addressed in future research on this issue. Firstly, two types of undesirable outputs were used, based on the data available, but more undesirable outputs can be considered, such as noise. Secondly, we have not taken into account contextual variables beyond the control of management, such as the age of the plant, which may also affect its technical efficiency. Finally, the data set is short and therefore the conclusions are limited. In order to generalise, a larger data

set would be necessary. More research is needed to confirm the present findings.

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